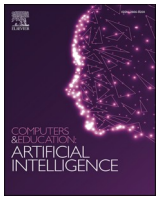
Computers and Education: Artificial Intelligence 7 (2024) 100286

Contents lists available at ScienceDirect

Computers and Education: Artificial Intelligence

journal homepage: www.sciencedirect.com/journal/computers-and-education-artificial-intelligence



The effect of student acceptance on learning outcomes: AI-generated short videos versus paper materials

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ARTICLE INFO

Keywords:
Student acceptance
Learning outcomes
AI videos
Short videos
Foreign language learning

ABSTRACT

The use of video and paper-based materials is commonly widespread in foreign language learning (FLL). It is well established that the level of acceptance of these materials influences learning outcomes, but there is lack of evidence regarding the use and related impact of videos generated by artificial intelligence (AI) on these aspects. This paper used linear mixed models and path analysis to investigate the influence of student acceptance of AI-generated short videos on learning outcomes compared to paper-based materials. Student acceptance was assessed based on perceived ease of use (PEU), perceived usefulness (PU), attitude (A), intentions (I), and concentration (C). The results indicate that both AI-generated short videos and paper-based materials can significantly enhance learning outcomes. AI-generated short videos are more likely to be accepted by students with lower pre-test scores and may lead to more significant learning outcomes when PEU, PU, A, I and C are at higher levels. On the other hand, paper-based materials are more likely to be accepted by students with higher pre-test scores and may lead to more significant learning outcomes when PEU, PU, A, I and C are at lower levels. These findings offer empirical evidence supporting the use of AI-generated short videos in FLL and provide suggestions for selecting appropriate learning materials in different FLL contexts.

1. Introduction

According to the Cognitive Theory of Multimedia Learning, people learn better from text and pictures than from text alone (Mayer, 2020). In comparison to text and audio, the use of video in learning environments offers students a more comprehensive and engaging approach to understanding learning materials (Hung, 2016). Among these video-based materials, short videos have emerged as an innovative pedagogical approach that have been gaining popularity across various educational settings in recent years (Kruger & Doherty, 2016). This growth can be largely attributed to the widespread usage and daily reliance on digital technologies and social media platforms (Jong et al., 2020; Kaye et al., 2022; Zahirović Suhonjić et al., 2019).

Evidence suggests that regardless the video length, students' average engagement time does not exceed 6 min, with the highest engagement observed when videos are only kept under 3 min (Guo et al., 2014). This trend is supported by feedback from students, who prefer shorter videos and are strongly interested in specific video formats, such as practical demonstrations (Choe et al., 2019). Furthermore, recent investigation on videos containing scientific information, particularly on representative social media platforms like TikTok, reveal that most of these videos are less than a minute and their contribution to knowledge construction is beginning to be studied (Nguyen & Diederich, 2023).

Therefore, shorter videos are attractive not only because of their brevity but also because they can be better planned than longer videos (Guo et al., 2014). There are already some benefits that highlight the importance of incorporating short videos into educational practice. For example, short videos can improve students' learning outcomes and their desire to revisit the content (Carmichael et al., 2018), and are more effective than longer videos in managing and reducing students' cognitive load (Lee et al., 2021).

Most studies on short videos have focused on contrasting them with longer video formats (Afify, 2020; Manasrah et al., 2021; Yu & Gao, 2022), with few studies examining the effect of short videos on learning

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https://doi.org/10.1016/j.caeai.2024.100286
Received 5 June 2024; Received in revised form 22 August 2024; Accepted 24 August 2024
Available online 27 August 2024
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outcomes and student acceptance in comparison to paper-based materials. The existing ones yield mixed results regarding the effectiveness of short videos versus paper-based materials (Tarchi et al., 2021; Van Der Meij & Van Der Meij, 2014).

Recent advances in generative artificial intelligence (AI) technologies have expanded capabilities into areas previously considered unattainable, including the production of short videos (Leiker et al., 2023). Current AI for video generation facilitate the conversion of presentations, websites, and text content into video format (UNESCO, 2023). This means that videos can be generated with the same content as paper-based learning materials easily. However, the use of AI-generated short videos in educational settings is still in its initial stages. The learning outcomes and acceptance of these videos in foreign language learning (FLL) remain unclear.

Therefore, given the rapid development of AI technology, which enables the rapid conversion of paper-based content into video format, and the ongoing debate about the effectiveness of short videos versus paper-based materials, a comparison between AI-generated short videos and paper-based materials may have considerable empirical significance. Furthermore, the extent to which the acceptance of AI-generated short videos correlates with improved learning outcomes, particularly in the context of FLL, remains unclear. Consequently, this study aims to address this gap by comparing the learning outcomes and student acceptance of AI-generated short videos with those of paper-based materials.

1.1. Learning outcomes and acceptance of short video compared to paper-based materials

Video and paper are two commonly used materials in learning, and their impact on learning outcomes and acceptance has been consistently compared. Tarchi et al. (2021) compared three learning conditions differing for modality: narrated video versus subtitled video versus text with graphics, and assessed their impact on students' learning outcomes. The video was created by an educational publisher and had a duration of 6 min. The results indicated that immediate and delayed comprehension were similar across all conditions. Conversely, Van Der Meij and Van Der Meij (2014) analysed the presentation of software instructions via video and via paper. They compared four tutorial configurations: paper-based, paper preview and video procedure, video preview and paper procedure, and video-based. The videos were self-made and lasted for 2 min. The results of the study revealed significant and substantial improvements across all conditions. However, participants in the paper-based condition exhibited lower performance compared to the other conditions. Instead, video worked better for preview tasks and favoured the presentation of software instructions.

In the field of FLL, Redzioch-Korkuz (2019) conducted a study on the impact of using subtitled short films versus paper-based materials on vocabulary acquisition. The findings showed that while there were slight differences in the overall performance, these did not reach statistical significance. Nevertheless, students in the video group exhibited a greater enthusiasm for learning, as they were able to facilitate easier retention. Zhang et al. (2021) conducted a study to explore the differences in learning outcomes among second language learners who used short video clips or paper-based materials for vocabulary and phrase acquisition. The results revealed that students made significant progress and showed a positive attitude towards learning when using video-based materials. Subsequently, Huang et al. (2022) investigated students' perceptions of using multimodal materials compared to paper-based materials for foreign language phrases learning. The videos were segments from films and television programmes. The findings indicated that both groups demonstrated substantial improvements, with students exposed to video-based materials demonstrating better performance and a positive attitude towards learning.

The multimodal nature of short videos fosters effective and engaging learning experiences (Choe et al., 2019). Short videos not only can increase viewer engagement but also enhance the likelihood of repeated usage (Carmichael et al., 2018). Furthermore, short videos have the capacity to simulate professional contexts (Ogea, 2020), and can be employed to enhance motivation and participation in FLL (Larreta-Azelain & Monje, 2016).

However, Jarvis and Szymczyk (2009) investigated students' attitudes towards learning grammar in a self-paced environment and their preferences for learning materials. They found that students generally preferred to use paper-based materials. Isla-Montes et al. (2022) indicated that when comparing the effectiveness of the writing task in paper and digital formats, paper-based materials were found to be more advantageous in enhancing students' language proficiency. While digital materials facilitated student interaction, they may have not effectively supported the development of students' communicative skills. Yu et al. (2022) also concluded that participants exhibited enhanced reading comprehension accuracy when reading from printed paper compared to reading from a mobile device.

Consequently, it is challenging to reach a definitive conclusion regarding the comparative merits of short video and paper-based materials in diverse contexts and for various purposes. Different studies focus on comparing these two types of materials, but none uses AI-generated short videos as a video mode.

1.2. Learning outcomes and acceptance of AI-generated videos compared to human videos

Generative AI represents a form of AI technology that is capable of autonomously generating content encompassing all forms of human cognitive representations based on prompts provided within natural language dialogue interfaces (UNESCO, 2023). Its rapid advancement underscores its role in supporting learning and well-being (Pataranutaporn et al., 2021). At the present time, video-generating AI technologies can transform a variety of content, including presentations, websites, and textual content, into video formats effortlessly (UNESCO, 2023). A recent study compared the impact of AI-generated videos and human videos on learners' content acquisition and learning experiences (Leiker et al., 2023). The findings revealed no significant differences between the two conditions regarding learning outcomes and participants' perceptions of the videos. Consequently, tasks that were previously considered to be beyond the capabilities of AI can now be accomplished.

Prior to the integration of AI-generated speech and avatars in videos, a series of studies have been conducted to compare the effectiveness of virtual speech and avatars. Craig and Schroeder (2017) compared presenters with modern speech engine and human voice. The results indicated that there were no significant differences between the two in facilitating learning. It was emphasized that while learners may perceive differences in the voices of the presenters, these distinctions are insufficient to impact their trust in the information presented. Their subsequent research demonstrated that, despite participants reporting a preference for human voice, no significant differences were evident in learning outcomes or cognitive efficiency measures (Craig & Schroeder, 2019). Similarly, Davis et al. (2019) demonstrated that even in non-native contexts, modern computer-generated speech can be as effective as human voice in knowledge retention. Furthermore, Vallis et al. (2023) discovered that AI avatars are perceived as effective tools for content delivery, with students demonstrating a high level of satisfaction and at times even regarding them as high-quality delivery mechanisms.

Although some studies have showed that virtual agents may produce comparable learning outcomes, they may also influence learners' trust and perceptions in disparate ways (Chiou et al., 2020). It is crucial to acknowledge that the efficacy of human voices may not necessarily exceed that of modern computer-generated speech if auditory elements are not effectively conveyed in accordance with audience needs (Davis et al., 2019). Conversely, AI instructors are capable of consistently

delivering effective instructional content, thereby avoiding the potential for emotional fluctuations (Kim et al., 2022).

Therefore, given the potential for AI-generated videos to achieve comparable learning outcomes and acceptance as human videos, and the capability of AI technology to swiftly convert paper-based content into video format, AI-generated videos hold notable potential for use in a wide range of educational settings. Consequently, a comparison between AI-generated short videos and paper-based materials may have considerable empirical significance. Moreover, the relations between the acceptance of AI-generated short videos and enhanced learning outcomes, particularly in the context of FLL, remains unclear and warrant further research.

1.3. The Technology Acceptance Model in education

The Technology Acceptance Model (TAM) served as a theoretical framework employed to elucidate and predict the acceptance of novel technologies by individuals (Davis et al., 1989). This framework has been repeatedly affirmed as suitable for delving into the variables influencing technology acceptance within educational research. For instance, Liu et al. (2009) combined the classic TAM with flow theory and media richness theory. Students interacted with one of three combinations: text, streaming audio, or streaming video. Their findings confirmed that perceived ease of use predicts perceived usefulness, while perceived usefulness and attitudes predict intention. Additionally, richer content combinations were associated with increased attention levels, though the correlation with perceived usefulness showed mixed results.

Huang et al. (2012) employed the TAM to explore students' perceptions of a self-developed English vocabulary learning system. Their results indicated that active students were interested in perceived usefulness, while passive students were interested by perceived ease of use. Tsai (2015) used the TAM to evaluate the impact of course management system on English writing teaching, revealing positive outcomes mainly attributed to technical support, perceived usefulness, perceived ease of use, and attitude. Nagy (2018) extended the TAM to examine student video usage determinants and learning satisfaction. Results showed that perceived usefulness, attitude, and internet self-efficacy directly impacted video usage, while learning satisfaction was influenced by learner interaction, perceived ease of use, and learning performance. Moreover, video usage significantly affected learning performance and satisfaction. Pal and Patra (2021) proposed an integrated the TAM to understand students' adoption of digital technology for learning. Their study revealed a strong correlation between video learning success, students' perception, system usage, and individual characteristics.

Against this background, the application of the TAM proved suitable to analyse students' acceptance of AI short videos, thereby providing insights into the factors that facilitate or hinder their acceptance in the context of this study.

1.4. Study aim

The study aims to compare the learning outcomes and student acceptance of AI-generated short videos with paper-based materials in the context of FLL with the following research question: How does student acceptance of AI-generated short videos influence learning outcomes in FLL compared to paper-based materials?

Additionally, the study tests six hypotheses based on Liu et al. (2009). H1: perceived ease of use (PEU) is positively associated with perceived usefulness (PU); H2: PEU is positively associated with attitudes (A); H3: PU is positively associated with A; H4: PU is positively associated with intentions (I); H5: A is positively associated with I; H6: Concentration (C) is positively associated with I.

2. Methods and materials

2.1. Participants and procedure

This is an exploratory study comprising 20 students who were studying Portuguese as a foreign language at the B1 proficiency level in a mid-to-large public Higher Education Institution on the central coast of Portugal. These participants were randomly divided into two groups: the video group (n = 10) and the paper group (n = 10). The video group watched AI-generated short videos, while the paper group used paper-based materials with content that matched the videos. Participation in the study was voluntary, anonymous, and fully consensual, with approval obtained from the Ethics and Deontology Committee of the University. Each participant was exposed to the experimental materials four times. The experimental instrument included a pre-test, a post-test, and a survey of acceptance. Data collection took place in the academic year 2023/24, during regular classes in two B1 level courses.

2.2. Learning materials

The learning content was taken from a textbook on European Portuguese oral expression (Boléo & Dourado, 2019). Two experienced Portuguese (as foreign language) teachers identified specific chapter topics according to the students' proficiency level. Four paper-based materials were produced, in accordance with the B1 level content outlined in the textbook. Each material contained 5 to 6 everyday expressions used in European Portuguese.

Subsequently, four paper-based materials were converted into short video of approximately 40 s, using the Synthesia platform. This platform allows for the generation of videos featuring dynamic characters through script inputs and supports the use of these videos in educational research. Given the effectiveness of multimedia learning principles in video design (Mayer, 2021), these principles were used as the basic framework for video production. For instance, most harmonious combination of female avatar and voice were selected, following the principles of voice, image, and embodiment. The video was then edited to include subtitles, prompts, background standardisation and pacing adjustments. These modifications addressed concerns related to coherence, signalling, spatial contiguity, segmenting, and multimedia principles. The primary goal of these improvements was to reduce the potential impact of external variables on video design, thereby ensuring absolute consistency across all videos beyond the learning content.

2.3. Technology acceptance model

Considering that the objective of this paper was not to identify new external variables to extend the TAM, we used the framework previously expanded by Liu et al. (2009) to compare the factors influencing the acceptance of videos and paper materials. This integrated framework measured participants' PEU, PU, A, I and C, using a questionnaire with 17 seven-point Likert-scale items ranging from 'strongly disagree' (1) to 'strongly agree' (7) (see Table 1). The questionnaire demonstrated good and excellent global reliability with our sample, with a Cronbach's alpha coefficient of PEU ($\alpha = .929$), PU ($\alpha = .959$), A ($\alpha = .897$), I ($\alpha = .828$) and C ($\alpha = .926$) (Nunnally & Bernstein, 1994).

2.4. Synthetic dataset generation

The generation of synthetic data involves extracting information from actual respondent datasets and reconstructing the outcomes into a collection of synthetic datasets for public use (Raghunathan, 2020). In the field of education, synthetic data is used to quickly create complex and stratified datasets, addressing ethical and privacy risks in service development processes (Berg et al., 2016). Furthermore, synthetic data can be employed to substitute missing data or facilitate disambiguation processes (Ferreira et al., 2012), thereby enabling the generation of

Table 1
Scales of student acceptance.

Scale name	Item
PEU1	It is easy for me to remember how to carry out tasks using the learning material.
PEU2	I believe that it is easy to get the learning material to do what I want it to do.
PEU3	My interaction with the learning material is clear and understandable.
PEU4	Overall, I believe that the learning material is easy to use.
PU1	Using the learning material improves my schoolwork performance.
PU2	Using the learning material improves my productivity.
PU3	Using the learning material enhances my effectiveness as regards schoolwork.
PU4	Overall, I find that using the learning material is useful in my schoolwork.
A1	I like using the learning material.
A2	The learning material is fun to use.
A3	The learning material provides an attractive working environment.
I1	I intend to completely switch over to the learning material.
I2	I intend to increase my use of the learning material in the future.
I3	Assuming that I have access to the learning material, I intend to use it.
C1	I was absorbed intensely in the learning material.
C2	My attention was focused on the learning material.
C3	I was deeply engrossed in the learning material.

larger datasets than those feasible with real data alone. This allows for the identification of patterns that would otherwise remain obscured in the original dataset (Eno & Thompson, 2008).

In this study, synthetic data is used to address limitations in sample sizes. Nuβberger et al. (2021) evaluated the effectiveness of three commonly used generative modelling methods: Variational Autoencoders (VAE), Deep Boltzmann Machines (DBM), and Generative Adversarial Networks (GAN), under conditions of limited sample sizes. The results suggest that VAE and DBM are more suitable for handling small sample sizes compared to GAN. Importantly, synthetic data can exhibit statistically similar characteristics to real data and adheres to any logical validity constraints imposed on the real data (Raghunathan, 2020).

Given the limited sample size in our study, a VAE (Kingma & Welling, 2014) was employed to generate synthetic data from the collected measurements. We standardized the numerical data using the StandardScaler (Pedregosa et al., 2011) and then converted it into PyTorch tensors (Paszke et al., 2019). The encoder, a neural network, produced mean and log variance outputs. The decoder, with three layers, used a sigmoid function to generate data. During training, two distinct VAE models were trained, one for the video group and the other for the paper group. Throughout the training process, we iteratively adjusted the models to minimize the disparity between the generated data and the original dataset, ensuring the distribution of the new data points remained consistent. Finally, 300 synthetic data were generated for each of the video and paper groups, and the synthetic dataset for each group was formed by combining the original data with the generated synthetic data.

2.5. Data analysis

To investigate differences in learning outcomes and student acceptance regarding the use of AI-generated short videos versus paper-based materials, we used linear mixed models with restricted maximum likelihood estimation (REML) (Littell et al., 2006). The model included a random intercept for intercept ID to account for potential variability between participants. The total tests were measured by combining the scores from the four tests. Additionally, the scores from the first test were evaluated separately to ensure an unbiased response, as the total tests may have been influenced by carry-over effects. A path analysis was also performed using maximum likelihood with robust standard errors. The path analysis was based on a synthetic dataset to enhance the statistical inference and maintain the integrity and representativeness of the original data characteristics. The purpose of this analysis was to clarify the direct and indirect effects among PEU, PU, A, I, and C, and to identify the main paths that influence intention to use within each group, providing a comprehensive understanding of the variables that drive student acceptance.

3. Results

A mixed model was conducted with the first test and the total tests as dependent variables and condition (video-based and paper-based materials) and moment (pre-test and post-test) as independent variables. The main effect of the moment was found to be highly significant for the first test ($F(1,9) = 36.0$, $p < .001$) and the total tests ($F(1,9) = 66.3$, $p < .001$) in the video group. This was also highly significant for the first test ($F(1,9) = 57.5$, $p < .001$) and the total tests ($F(1,9) = 111$, $p < .001$) in the paper group. These results indicate that both materials significantly enhanced learning. Additionally, the interaction effect between 'condition✻moment' was not significant for either the first test ($F(1,18) = 0.053$, $p = .820$) or the total tests ($F(1,18) = 0.425$, $p = .523$). This indicates that the difference between the pre-test and post-test did not significantly vary between the two materials.

The student acceptance variables (PEU, PU, A, I and C) were then included as covariates in the previous model. The main effects of PEU, PU, A, I and C were found to be not significant for both the first test and the total tests. Similarly, the two-way interaction effects including 'condition✻moment' and 'condition✻PEU/PU/A/I/C' did not result in any significant interactions. However, there were exceptions within the three-way interactions 'condition✻moment✻PEU/PU/A/I/C', indicating complexities that require further investigation (See Table 2).

The first test results showed significant interactions for PEU, PU, A and C, while the variable I reached marginal significance. In relation to the total tests results and considering carry-over effects, there was a general decrease in the significance levels for all variables, although significant interactions were still observed for PEU and C, PU and I showed marginal significant interactions. However, A did not show significant interactions. It is important to highlight that despite the absence of significant differences in learning outcomes between the two materials, incorporating student acceptance variables as covariates in the analysis significantly influenced the variance in learning outcomes.

The distribution of learning outcomes between the two materials presents different mean levels of student acceptance (see Fig. 1). This visualization was conducted for both the first test and total tests. In both scenarios, it was observed that within the Mean-1-SD column, the use of paper-based materials demonstrated a more inclined trend in comparison to the AI-generated short videos. This indicates that paper-based materials may lead to more significant learning outcomes when PEU, PU, A, I and C are at lower levels. Conversely, within the Mean+1-SD column, AI-generated short videos demonstrated a more inclined trend in comparison to paper-based materials. This suggests that AI-generated short videos may lead to more significant learning outcomes when PEU, PU, A, I and C are at higher levels.

Fig. 2 provides an explanation for the observed results. In the video group, students with lower acceptance levels (blue line) scored higher in the pre-test for both the first test and the variables A, I, and C of the total tests. In contrast, students with higher acceptance levels (yellow line) reached lower pre-test scores, but the more inclined trend of the yellow line indicates their better learning outcomes. The results can be explained by the fact that AI-generated short videos may lead to more significant learning outcomes when PEU, PU, A, I and C are at higher levels.

In contrast, students in the paper group with lower acceptance levels (blue line) scored lower in the pre-test for both the first test and the total tests, while those with higher acceptance levels (yellow line) scored higher in the pre-test. The blue lines also indicate a more inclined trend, suggesting better learning outcomes for these students. The results can

Table 2
Three-way interaction results.

	First test				Total tests			
	F	Num df	Den df	*p*	*F*	Num df	Den df	*p*
condition ✻ moment ✻ PEU	19.679	1	16	< .001	7.688	1	16	.014
condition ✻ moment ✻ PU	5.882	1	16	.027	4.418	1	16	.052
condition ✻ moment ✻ A	4.643	1	16	.047	1.353	1	16	.262
condition ✻ moment ✻ I	4.049	1	16	.061	3.828	1	16	.068
condition ✻ moment ✻ C	8.565	1	16	.010	6.380	1	16	.022

Note: PEU (perceived ease of use), PU (perceived usefulness), A (attitude), I (intentions), C (concentration).

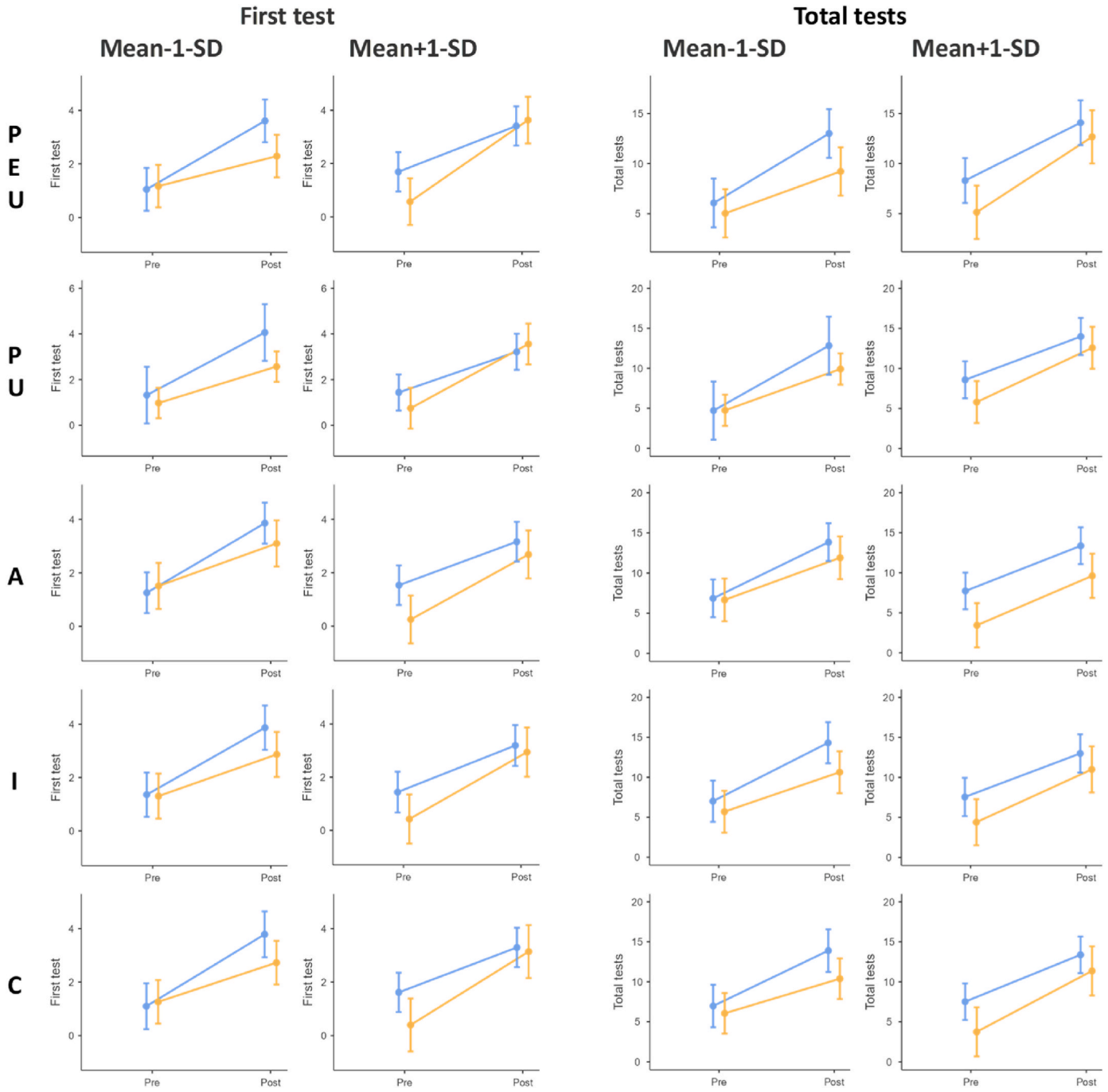

Fig. 1. Differences of learning outcomes divided by student acceptance variables. Note: ● (video group), ● (paper group), PEU (perceived ease of use), PU (perceived usefulness), A (attitude), I (intentions), C (concentration).

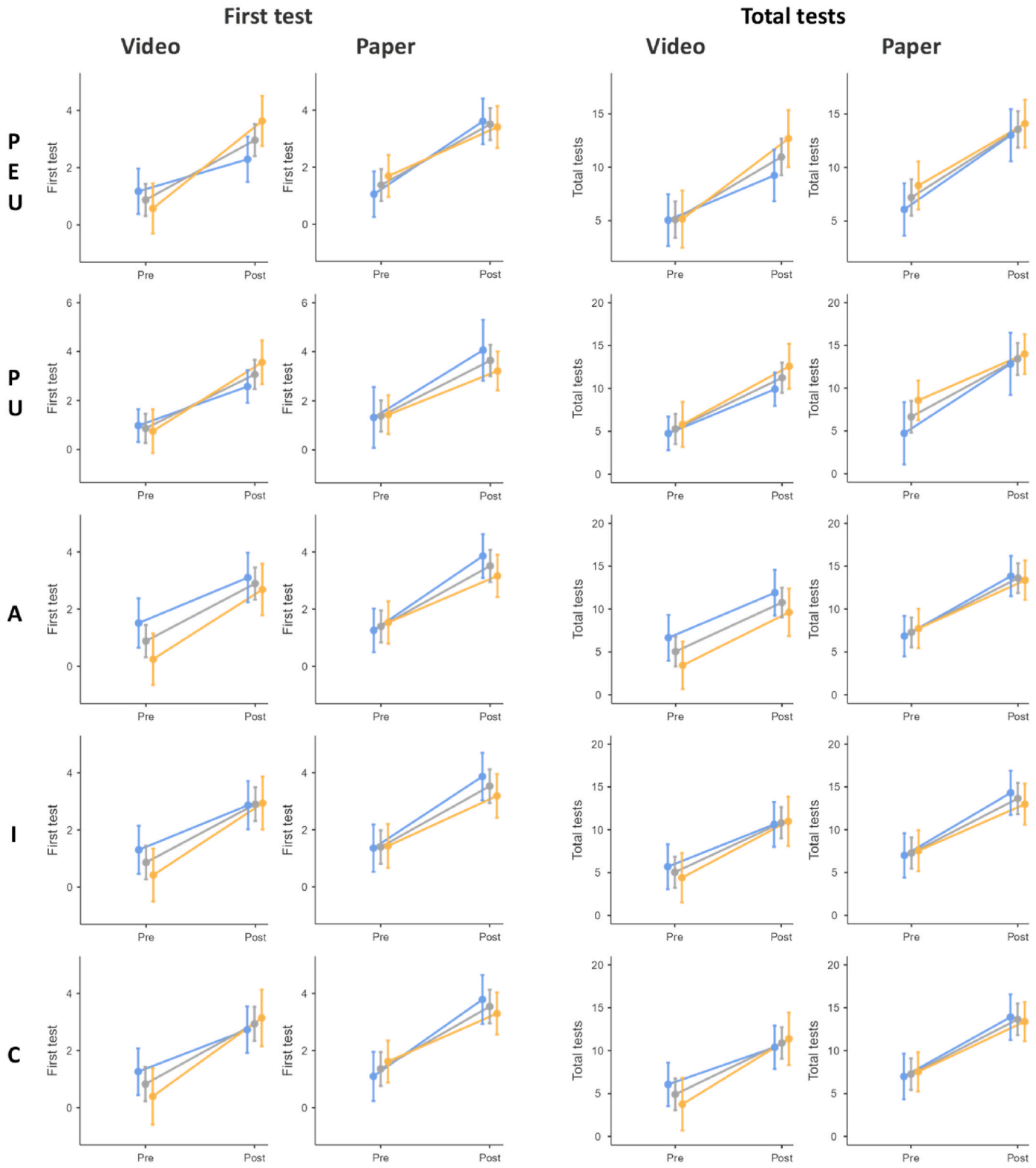

Fig. 2. Differences of learning outcomes according to learning materials. Note: (Mean-1-SD), (Mean), (Mean+1-SD), PEU (perceived ease of use), PU (perceived usefulness), A (attitude), I (intentions), C (concentration).

be explained by the fact that paper-based materials may lead to more significant learning outcomes when PEU, PU, A, I and C are at lower levels.

Therefore, in addition to the fact that students with lower pre-test scores may achieve better learning outcomes, the results also suggested that AI-generated short videos are more likely to be accepted by students with lower pre-test scores, whereas paper-based materials are more likely to be accepted by students with higher pre-test scores.

The linear mixed model results did not show any significant interactions for the variable I in both the first test and total tests. Additionally, the variable A did not even reach marginal significance in the total tests. To further explore the intrinsic relationships among

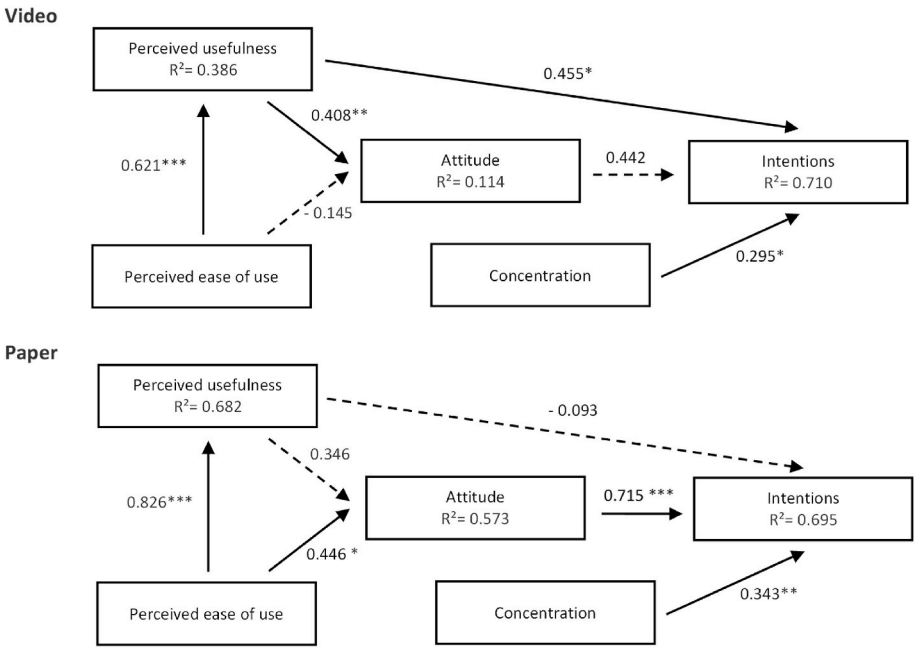

Fig. 3. Path analysis of PEU, PU, A, I and C for the two groups. Note: ***p<. 001, **p<. 01, *p<. 05, → significant path, ⇢ non-significant path.

acceptance variables and their impact on A and I, a synthetic dataset was used for path analysis (see Fig. 3). It is important to note that the path analysis aimed to investigate previously established paths (Liu et al., 2009) rather than validate new paths.

The path analysis results indicate that neither group was able to fully replicate all the proposed hypotheses, especially in relation to variables A and I. The variable A in the video group was not adequately explained by its predictors ($R^2 = 0.114$), particularly by the PEU ($\beta = -0.145$, $p = .484$). Additionally, the variable A had only a marginal influence on I ($\beta = 0.442$, $p = .057$). The results were consistent with previous findings from the linear mixed model, where the variable A showed no significant or marginally significant effects in the three-way interaction of the tests, distinguishing it from other variables. This suggests that other variables, not considered in this study, may have a greater influence on A.

Subsequently, an analysis of all paths leading to the variable I was conducted. Table 3 demonstrates that both groups had only one effective path leading to I. For the video group, the path was from PEU to PU to I ($\beta = 0.283$, $p = .020$). This relation suggests that student's perceived ease of use of AI-generated short videos enhances their perceived learning outcomes, thereby promoting the intention to use videos. This finding supports the results of the linear mixed models, indicating that at higher levels of acceptance, AI-generated short videos may lead to more significant learning outcomes compared to paper-based materials.

However, the effective path for the paper group was from PEU to A to I ($\beta = 0.319$, $p = .038$). This suggests that the ease of use of paper-based materials enhances students' positive attitudes towards them, subsequently influencing their intentions to use them. However, PU cannot predict A ($\beta = 0.346$, $p = .181$) or I ($\beta = -0.093$, $p = .677$). PU refers to learners' perception of the materials' ability to enhance learning outcomes. This indicates that even if students believe paper-based materials can improve their performance, this belief does not necessarily result in a more positive attitude towards the materials or a stronger intention to use them.

4. Discussion

The present study aimed to answer the following research question: How does student acceptance of AI-generated short videos influence learning outcomes in FLL compared to paper-based materials?

The results found significant main effects related to the test moment for both the first test and the total tests. These results confirmed that both AI-generated short videos and paper-based materials significantly enhanced learning, in line with the findings of previous studies on the impact of short videos and paper-based materials on learning (Huang et al., 2022; Tarchi et al., 2021; Zhang et al., 2021). The results further supported the findings that AI-generated videos can foster learning outcomes (Kim et al., 2022; Leiker et al., 2023; Vallis et al., 2023).

However, the interaction between material type and moment showed no significant difference for either the first or the total test, indicating that the two materials did not differ significantly in terms of enhancing learning outcomes. This was in line with Clark (1983) who argued that the educational media themselves do not directly influence

Table 3
Paths to intentions.

Label	Description	Estimate	SE	95% Confidence Intervals		β	z	p
				Lower	Upper			
Video1	(PEU ⇒ PU ⇒ A ⇒ I)	0.144	0.106	−0.064	0.352	0.112	1.358	.174
Video2	(PEU ⇒ PU ⇒ I)	0.364	0.157	0.057	0.671	0.283	2.322	**.020**
Video3	(PEU ⇒ A ⇒ I)	−0.082	0.129	−0.335	0.170	−0.064	−0.639	.523
Video4	(PU ⇒ A ⇒ I)	0.168	0.118	−0.063	0.398	0.180	1.425	.154
Paper1	(PEU ⇒ PU ⇒ A ⇒ I)	0.267	0.226	−0.176	0.710	0.204	1.183	.237
Paper2	(PEU ⇒ PU ⇒ I)	−0.100	0.251	−0.593	0.392	−0.077	−0.399	.690
Paper3	(PEU ⇒ A ⇒ I)	0.417	0.201	0.023	0.811	0.319	2.072	**.038**
Paper4	(PU ⇒ A ⇒ I)	0.449	0.368	−0.273	1.171	0.247	1.220	.223

Note: PEU (perceived ease of use), PU (perceived usefulness), A (attitude), I (intentions), C (concentration).

learning outcomes, but that it is the teaching strategies and content that play a crucial role. Thus, while the positive influence of multimedia on FLL is widely recognized (Lee & Mayer, 2018), there are still conflicting results regarding the effectiveness of different input modalities (Zhang & Zou, 2022). Previous studies have yielded mixed results regarding the comparative effectiveness of short videos and paper-based materials (Tarchi et al., 2021; Van Der Meij & Van Der Meij, 2014). This situation has also been observed in the context of FLL (Huang et al., 2022; Redzioch-Korkuz, 2019; Zhang et al., 2021). However, it is important to note that these studies separate the influence of learning outcomes and student acceptance of short videos and paper-based materials. They do not correlate the acceptance of short videos with improved learning outcomes.

Our results indicated that student acceptance may play different roles under different learning materials and influence learning outcomes. This is consistent with the findings of previous studies, for instance, Tsai (2015) who assessed the impact of course management systems on English writing instruction, highlighting effects linked to technical support, perceived usefulness, ease of use, and attitude. Nagy (2018) investigated the factors influencing student video usage and learning satisfaction. The findings indicated that perceived usefulness, attitude, and self-efficacy were associated with video usage. Additionally, learner interaction, ease of use, and performance were identified as key factors influencing learning satisfaction. Pal and Patra (2021) also revealed strong correlations between video learning success, perception, system usage, and individual traits.

Our results indicated that when levels of PEU, PU, A, I and C are low, paper materials may produce more significant learning outcomes; conversely, when levels of these variables are high, AI-generated short videos may be more effective. We have explained the reason for the increased learning outcome, as both levels of acceptance in different materials correspond to students with lower pre-test scores. In other words, both materials enable students with lower pre-test scores to achieve higher learning outcomes. Even students with lower pre-test scores, who were initially less willing to use paper materials, did not experience a negative impact on their learning outcomes. Therefore, our findings support the notion that lower performing students may have significant potential for improvement compared to higher performing students (Yang & Li, 2018).

A more important observation is that AI-generated short videos were more likely to be accepted by students with lower pre-test scores, while paper-based materials were more likely to be accepted by students with higher pre-test scores. It should be noted that this comparison did not imply that students with higher pre-test scores preferred paper-based materials to video ones, but rather that students with higher pre-test scores were more receptive to paper-based materials compared to students with lower pre-test scores.

Videos are more likely to be accepted by students, as both attitude and ability play a crucial role in determining where attention is focused (Schmidt, 2010). In our AI-generated short videos, both speech and avatar were produced by AI. It is well-established that videos, as a multimodal material, engage both visual and auditory channels. Therefore, improper design of multimodal elements in videos may lead to a higher cognitive load compared to paper-based materials, thereby affecting learning outcomes (Mayer, 2020). Within a group of students exposed to identical instructional designs, differences in prior knowledge represent the primary source of cognitive diversity among individuals (Sweller, 2024). Thus, while various cognitive elements contribute to individual variations, disparities in acquired knowledge significantly influence how individuals process information. Consequently, in contrast to students with higher pre-test scores, those with lower pre-test scores face greater demands on their memory retention (Sweller, 2024). Therefore, if AI-generated speech and avatars were to exert a degree of negative influence on students' cognition, it would be unlikely that individuals with lower pre-test scores would exhibit higher levels of acceptance or achieve superior learning outcomes. As emphasized in our introduction, tasks previously considered beyond the capabilities of AI can now be accomplished effortlessly (Kim et al., 2022; Vallis et al., 2023), with AI-generated videos achieving comparable levels of learning outcomes and perception as human videos (Leiker et al., 2023).

The path analysis results indicated that, for the video group, the path from PEU via PU to I was significant. This relation suggests that perceived ease of use of AI-generated short videos enhances students' perceived learning outcomes, which in turn promotes their intention to use AI-generated short video. This finding reinforces that AI-generated short videos not only facilitate learning outcomes but also influence students' perceptions of their learning outcomes positively.

An unexpected finding, for the AI-generated videos was that the path from PEU to I, mediated by A, was not significant. Furthermore, the variable A showed no significant or marginally significant effects within the three-way interaction in the tests, setting it apart from other variables in the study. These findings challenge the assumption that the perceived ease of use of AI-generated short videos necessarily foster more positive attitudes or stronger intentions to use. Additionally, it implies that other variables, not considered in this study, such as video duration, AI speech and AI avatar, may have a greater influence on A. However, the current data do not directly prove whether this entails a higher or lower level of acceptance, nor is it possible to precisely determine the other variables that affect A. These aspects warrant further investigation.

Additionally, for the paper-based materials, the path from PEU via A to I was significant. This suggests that the ease of use of paper-based materials enhances students' positive attitudes towards them, subsequently influencing their intentions to use them. Nonetheless, students did not necessarily translate their perceptions of the potential learning outcomes of paper-based materials into increased intentions to use or more positive attitudes towards these materials. Therefore, it is recommended that teachers not only emphasise the effectiveness of learning materials but also focus on the positive acceptance towards using them.

Finally, we consider the implications of this study for educational theory and pedagogy. This study validates the effectiveness of short videos and AI-generated ones as pedagogical tools. It suggests that AI-generated content can align with multimedia learning theories, thereby enhancing our understanding of how AI technologies can improve educational practices. Additionally, our findings underscore the critical role of students' acceptance of various types of learning materials on their learning outcomes. This emphasizes an important pedagogical implication that teachers should consider regarding the interplay between the effectiveness of learning materials and student acceptance. In other words, instructional strategies should include an understanding of how students perceive and interact with learning materials, even within an AI-enhanced learning environment. Furthermore, our study provides empirical evidence supporting the flexible use of AI-generated short videos alongside traditional paper-based materials, consistent with the theory of differentiated instruction. By leveraging this flexibility, teachers can optimize learning outcomes and foster more inclusive and effective educational environments.

4.1. Limitations

This study has inherent limitations. First, the research sample mainly consisted of learners at a lower proficiency level in Portuguese, which limits the generalizability of the study's findings to foreign language learners of different proficiency levels and learners in other disciplines. Second, the sample size was limited, which may have introduced bias in predictive effectiveness, despite the use of synthetic data to compensate for statistical inadequacies.

5. Conclusion

This study aimed to investigate the influence of student acceptance

of AI-generated short videos on learning outcomes in FLL compared to paper-based materials. The results indicate that both AI-generated short videos and paper-based materials can significantly enhance learning outcomes. AI-generated short videos are more likely to be accepted by students with lower pre-test scores and may lead to more significant learning outcomes when PEU, PU, A, I and C are at higher levels. On the other hand, paper materials are more likely to be accepted by students with higher pre-test scores and may lead to more significant learning outcomes when PEU, PU, A, I and C are at lower levels. Additionally, for AI generated short videos, the path from PEU via PU to I was significant. For the paper-based materials, the path from PEU via A to I was significant. To improve the external validity of the study, future research should include more participants from diverse educational backgrounds and proficiency levels. Furthermore, the PEU of AI-generated short videos did not result in more positive A. Therefore, it is necessary to investigate other variables such as video duration, AI speech and AI avatar, that may have a greater influence on A in further studies. In summary, this research contributed to the existing literature on AI-generated short videos and their integration into educational contexts. The empirical evidence presented in our findings supported the use of AI-generated short videos in FLL and provided suggestions for selecting appropriate learning materials in different contexts of FLL.

Funding

This work is financially supported by National Funds through FCT – Fundação para a Ciência e a Tecnologia, I.P., under the project 2022.14365.BD, 2021.03379.CEECIND and UIDB/00194/2020.

Ethical approval

The study was approved by the University's Ethics and Deontology Committee under number 60-CED/2023. Informed consent was obtained from all participants and their privacy rights were strictly observed.

Data availability

The data are not publicly available due to privacy or ethical restrictions.

CRediT authorship contribution statement

Yidi Zhang: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Margarida Lucas:** Writing – review & editing, Supervision, Resources, Methodology. **Pedro Bem-haja:** Writing – review & editing, Formal analysis, Data curation. **Luís Pedro:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Acknowledgements is extended to Dr. Carlos Morais and Dr. Sara Pita of the Department of Languages and Cultures at the University of Aveiro for their invaluable assistance in recruiting participants for this study.

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